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Baseline Evaluation of Backpropagation Artificial Neural Network for Visual Image-Based Vehicle Type Classification

Rika Harman[1,2]*, Imam Riadi[3], Abdul Fadlil[4]
[1*]Department of Informatics, Universitas Ahmad Dahlan, Yogyakarta, Indonesia, [2]Department of Informatics, Universitas Riau Kepulauan, Riau, Indonesia. [3]Department of Information System, Universitas Ahmad Dahlan, Yogyakarta, Indonesia. [4]Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta, Indonesia.

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ABSTRACT

For effective transportation management, technology-based solutions are needed due to the growing number of cars in metropolitan areas. Based on digital picture data, this paper suggests a vehicle classification model that makes use of Artificial Neural Networks (ANN) and the backpropagation technique. An input layer, a hidden layer with 64 sigmoid-activated neurons, and an output layer with 7 softmax-activated neurons make up the feedforward neural network model. 16,185 photos from eight different car classes—Hummer, Toyota Innova, Hyundai Creta, Suzuki Swift, Audi, Mahindra Scorpio, Rolls-Royce, and Tata Safari—make up the dataset, which was obtained from Roboflow Inc. The data is divided 80:20 between testing and training. Vehicle dimensions, the primary RGB color, the number of axles, and license plate recognition are examples of input features. Categorical crossentropy loss and gradient descent are used to train the model. The evaluation's findings indicate 100% test accuracy and 85% validation accuracy at epoch 28. Strong performance is shown by precision, recall, and F1-score; yet, in visually comparable classes, small errors do occur. These results show that backpropagation-based artificial neural networks (ANNs) are useful for classifying vehicles and can be used in traffic monitoring and automated parking systems.

Corresponding Author:
Rika Harman,
Department of Informatics, Universitas Ahmad Dahlan,
South Ring Road, Yogyakarta 55191, Indonesia.
E-mail:2436083022@webmail.uad.ac.id

1. INTRODUCTION.

According to projections, Indonesia's motorized vehicle population has grown significantly in recent years, from approximately 120 million units in the previous year to a greater amount in 2023. Numerous facets of life are directly impacted by this surge, such as the rise in air pollution, traffic jams, and the need for an efficient transportation management system. Automatic vehicle type recognition and classification is therefore crucial for traffic monitoring, intelligent transportation systems, and the development of data-driven transportation policies. There is an immediate need for a more effective transportation system due to the growing number of automobiles and their detrimental effects, such as traffic and pollution. This need in turn shows the limitations of present technology [1], [2], [3].

The development of artificial intelligence (AI) and image processing-based vehicle classification systems has been the subject of numerous studies. With differing degrees of success, methods including Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) have been employed. However, these approaches frequently still struggle with accuracy and gencomputability on complicated data [4], [5]. Specifically, the majority of earlier research has concentrated on classifying things that are still or that were photographed in optimal lighting. A neural network-based vehicle classification system with backpropagation, for instance, has been demonstrated in experiments to attain an accuracy of up to 87.5%; however, this system has not been extensively evaluated in real-world scenarios with notable differences in background, illumination, and viewing angle. Furthermore, a number of other research [6], [7] focused more on the classification of non-visual data, making them less useful for image-based vehicle processing. A major research vacuum is created by the shortcomings of current approaches, particularly when it comes to handling dynamic real-world settings [8], [9]. Prior research on ANN-based car classification has mostly used small datasets gathered in controlled settings, which has led to models that are less reliable in real-world settings. By assessing ANN performance on a sizable dataset comprising a variety of photos with different lighting conditions, backgrounds, and viewing angles, our study fills this research vacuum. In order to lay the groundwork for the future development of intelligent transportation systems, the goal is to create a baseline assessment that accurately depicts actual traffic circumstances.

The primary issue in this study is the lack of an image-based system for classifying vehicles that can function well in dynamic real-world environments [10], [11]. Reduced categorization accuracy is frequently the result of issues including visual differences in viewing angle, lighting intensity, and background [12]. Furthermore, there are still issues with the ANN model's generalization and training efficiency that have not been fully resolved [13].

The primary motivation behind this research is the requirement for a reliable and accurate vehicle categorization system in a variety of environmental situations [14], [15], [16]. A system that can accurately and instantly categorize cars is crucial given the growing use of automated traffic monitoring and intelligent transportation systems. A possible way to get over the aforementioned restrictions is to use ANN with backpropagation algorithms [17], [18]. Although this method has demonstrated efficacy in pattern recognition and image classification across a range of applications, more research is still needed to determine how well it applies to the categorization of vehicle types in light of changing environmental conditions [19], [20].

Although backpropagation artificial neural networks offer a lot of promise, an analysis of earlier research indicates that issues with generalization and training efficiency still exist. Activation function, learning rate, and neuron count are just a few of the variables that have been shown in numerous studies to significantly affect network effectiveness. To increase classification accuracy, feature extraction methods and data pretreatment are particularly crucial [21]. Therefore, to improve the performance of the vehicle classification system, this research will focus on refining the ANN architecture and its training parameters.

The actual necessity for a vehicle categorization system that is accurate, adaptable, and applicable to a range of field settings [22] s what makes this research so urgent. This is particularly pertinent in light of the growing need for intelligent, technology-based transportation systems, particularly in Indonesia's large cities where traffic is complicated and vehicle quantities are high [23].

In light of this, the goal of this research is to create a backpropagation-based artificial neural network-based vehicle type classification system that can function effectively in a range of environmental circumstances [24]. Vehicle image data collecting, data preprocessing, feature extraction, ANN architecture design, backpropagation algorithm training, and system performance assessment are some of the actions that will be performed in this study. It is anticipated that this study will significantly advance Indonesia's development of automated traffic monitoring and intelligent transportation systems [25].

Prior research has examined the application of Particle Swarm Optimization (PSO) and other optimized backpropagation neural network techniques. Nevertheless, the traditional BPNN approach is still used in this study without the use of an optimization technique. This method improves our understanding of BPNN's baseline performance in vehicle type categorization from visual images. The results of this study are expected to serve as the basis for the development of optimization techniques such as PSO or advanced feature extraction techniques.

2. LITERATURE REVIEW

. A successful car ownership prediction model employing PSO-BPNN (Particle Swarm Optimization-Backpropagation Neural Network) was developed by Zhang et al. [26] PSO-BPNN can be used to overcome the limitations of conventional BPNN. The study's findings demonstrate a notable improvement in prediction accuracy and convergence speed when compared to alternative approaches. Future car ownership predictions can be examined using this model, particularly when considering sustainable development and urban transportation management. This study continues to use the traditional Backpropagation artificial neural network (BPNN) as the foundation for developing an image-based vehicle classification model, in contrast to Zhang's study, which use the PSO-BPNN optimization approach. As a result, this study acts as an initial assessment to gauge BPNN's fundamental performance prior to its development or comparison with more sophisticated strategies like PSO optimization techniques or sophisticated feature extraction methods.

Tianang et al. [27] developed a motor fault diagnosis and fault-tolerant control system for electric vehicles with distributed drivetrains using a Backpropagation Neural Network (BPNN) for fault detection and Sliding Mode Control (SMC) for fault-tolerant control based on Direct Yaw Moment Control (DYC).In their vehicle model, they took into account several motor failure scenarios as short circuit, open circuit, and shutdown and classified fault types using BPNN. The findings demonstrated that the SMC-based fault-tolerant control technique successfully preserved vehicle stability even when a motor failed, particularly when driving on slick or wet surfaces, and that the fault detection system was very accurate in recognizing motor conditions.

The goal of Song et al.'s research [28] is to increase forecast accuracy and convergence speed, particularly when calculating the number of vehicles in China. Backpropagation Neural Networks (BPNN) tuned with PSO are used in this study. For the PSO-BPNN model to attain an error rate of 1.41×10^{-8} and an R2 value of 0.96002, just three training iterations are needed. This model, which has a relative error between 0.023 and 0.083, shows a strong correlation between the expected and actual values. According to these findings, this model outperforms both traditional BPNN and models that have been tuned using techniques like GA-BPNN and WOA-BPNN.

By creating a more effective training technique and optimized network architecture, the study "Bi-Real Net: Enhancing the Performance of 1-Bit CNNs With Improved Representational Capability and Advanced Training Algorithms" by Bangyuan et al. [29] seeks to improve the performance of binary convolutional neural networks (CNNs). To address the accuracy and stability concerns of traditional binary CNNs, the authors of this study present a progressive training strategy, a customizable hyperbolic tangent activation function, and an enhanced binarization algorithm. Furthermore, they suggest altering the residual block structure to better fit binary operations. According to experimental results, this method approaches the performance of full-precision models while using less memory and executing fewer computations, successfully achieving an accuracy of up to 94.77% on the CIFAR-10 dataset.

The study "Vehicle Classification Based On Backpropagation Neural Network with Metric Parameters and Eccentricity" by Mayatopani et al. [30] classifies several kinds of vehicles, including cars, buses, and trucks, using digital photographs. To make the car item stand out from the background, the image is cropped at the start of the procedure. The Backpropagation Neural Network approach, which has an accuracy rate of 87.5%, is then used to classify the features that have been retrieved using metric parameters, including the vehicle's length, width, and eccentricity. During testing, this model demonstrates satisfactory results in identifying vehicle shapes while simply utilizing basic geometric cues. The researchers also offer some recommendations for future study enhancements, like utilizing deep learning techniques for improved outcomes, expanding the size of the training data, and adding extra variables like color and texture. This study classifies vehicle kinds using an Artificial Neural Network (ANN) and the backpropagation technique.

3. RESEARCH METHODE

16,185 car photos from eight different classes Hummer, Toyota Innova, Hyundai Creta, Suzuki Swift, Audi, Mahindra Scorpio, Rolls-Royce, and Tata Safari make up the dataset used in this study. The variety of vehicle kinds and real-world changes, including lighting, backgrounds, and viewing angles, led to the selection of the data, which was acquired from Roboflow Inc. It was split into 20% for testing (3,237 photos) and 80% for training (12,948 images) to guarantee accurate evaluation. To enhance model generalization, each image was downsized to 224 by 224 pixels, normalized to a range of 0–1, and enhanced using flipping and rotation. Implemented with Python 3.10 and the Keras library, the ANN model is composed of three layers: an input layer, a hidden layer with 64 sigmoid neurons, and an output layer with eight softmax neurons. The backpropagation technique was used for training with a batch size of 32, gradient descent optimization for 30 epochs, and categorical crossentropy as the loss function. Figure 1 depicts the general workflow of the ANN training procedure.

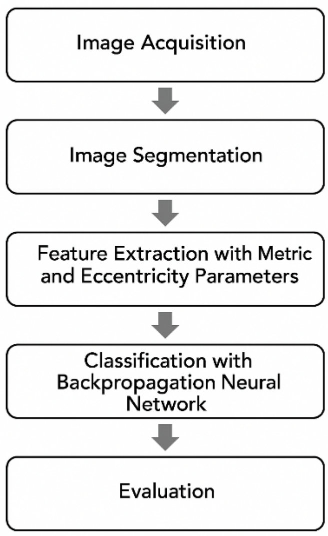

Figure 1. Research Diagram

The picture is a flowchart that shows the primary steps in the artificial neural network (Backpropagation Neural Network)-based vehicle classification process based on visual pictures. This graphic shows the order of the procedure from beginning to end and is composed of five major blocks that are stacked vertically and connected by gray arrows pointing downward. The process of acquiring or gathering vehicle photographs as input data is known as image acquisition, and it is the initial stage. The acquired images then proceed to the Image Segmentation phase, where they undergo processing to distinguish the vehicle object from the surrounding landscape. The process of extracting significant attributes or features from the vehicle object, such as dimensions (length, width) and eccentricity (degree of roundness of the object), which are helpful for the classification process, is then carried out. This is known as feature extraction with metric and eccentricity parameters. In order to classify automobiles into distinct categories, the collected features are fed into the ANN model in the fourth stage, Classification with Backpropagation Neural Network. At the evaluation stage, the classification results are finally examined in order to gauge system performance using metrics like recall, accuracy, and precision. The workflow for image processing for vehicle categorization is shown in this diagram in an organized, methodical, and understandable manner.

Image Segmentation

An essential stage in digital image processing is image segmentation, which separates the main object from the background or from other objects in the image. Finding the borders of regions that are comparable in shape, intensity, or pixel arrangement allows for this separation. A binary picture, or one with two values, is the end product of the segmentation process: the backdrop is represented by a value of 0 (black), and the desired object is represented by a value of 1 (white). Thresholding, a technique that establishes the threshold value to distinguish object pixels from background pixels, is the segmentation approach employed in this study. Selecting the appropriate threshold value is essential since it will dictate how well segmentation separates pertinent elements. Wati, Haviluddin, Puspitasari, Budiman, and Rahim claim that the thresholding technique works best when there is enough contrast between the background and the item.

Feature Extraction with Metric and Eccentricity Parameters

An essential step in a pattern recognition system is feature extraction, which seeks to identify distinctive characteristics of the objects under study. These characteristics are then used as input parameters in the classification stage to effectively distinguish one object from another. Shape features are among the most informative feature categories when it comes to image-based object detection. Two primary parameters—metric and eccentricity—are used in this work to derive shape features.

Metric parameters, which are frequently employed to characterize an object's roundness or compactness, are the ratio of an object's area to the square of its circumference. A perfect circle-like shape is indicated by metric values near 1, but a more complex or extended shape is indicated by smaller numbers. The metric can be expressed mathematically as [31]:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Explanation:

1. The number of correct positive predictions, or the cases that were forecasted as positive and are in fact positive, is known as TP (True Positives).
2. The quantity of false positive predictions, or cases that were anticipated to be positive but turned out to be negative, is known as FP (False Positives).

Therefore, precision quantifies the accuracy of the model's positive predictions. Precision levels go between 0 and 1, with a number nearer 1 denoting fewer false positive predictions. In situations like spam identification or disease diagnosis, when the repercussions of false positive predictions must be avoided, precision is particularly crucial. It's a formula that you wrote.When assessing a classification model's performance, recall (also known as sensitivity/true positive rate) is used.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Explanation:

1. The number of accurate positive predictions, or the cases that were anticipated to be positive and turn out to be so, is known as TP (True Positives).
2. The number of inaccurate negative predictions, or cases that were predicted as negative but turned out to be positive, is known as FN (False Negatives).

Therefore, precision quantifies the accuracy of the model's positive predictions. Precision levels go between 0 and 1, with a number nearer 1 denoting fewer false positive predictions. In situations like spam identification or disease diagnosis, when the repercussions of false positive predictions must be avoided, precision is particularly crucial. The F1-Score formula, a performance metric that aggregates Precision and Recall into a single score, is the one shown in the picture.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + \ Recall} \tag{3}$$

One evaluation metric used to assess a classification model's performance is the F1-Score, which is particularly useful when the dataset is unbalanced or has a notably varied proportion of positive and negative examples. The F1-Score is defined by a formula that is the harmonic mean of Precision and Recall. The accuracy of the model's positive predictions is indicated by precision, or the proportion of projected positives that are actually true. Recall, on the other hand, measures the model's ability to identify each actual positive case. The F1-Score is particularly useful when a balance between precision and recall is needed because the two can occasionally conflict. In certain situations, a model may have a high precision but a low recall, or the opposite may be true. Because it offers a thorough understanding of the model's ability in identifying positive cases, the F1-Score thus becomes a significant metric. A model that performs well is indicated by a value near 1, whereas a model that performs poorly is indicated by a value near 0.

Classification with Backpropagation Artificial Neural Networks

One popular supervised learning technique for classification tasks is the Artificial Neural Network (ANN) with the backpropagation algorithm. Three primary layer types—the input layer, the hidden layer, and the output layer—make up the fundamental architecture of an ANN. The input layer receives data that has been retrieved through the preprocessing and feature extraction procedures as a numerical representation of the item that needs to be categorized.

ANN uses the backpropagation technique to modify the weights between neurons in each layer during the learning process. This approach uses an iterative process with two primary phases—feedforward and backward—to optimize the network weights. Input data is processed forward through the network until a projected output is produced during the feedforward phase. Additionally, the backward phase uses the gradient descent approach to update the network weights by calculating the error between the actual target and the anticipated output [32]. Figure 2 depicts the architecture of the neural network utilized in this investigation.

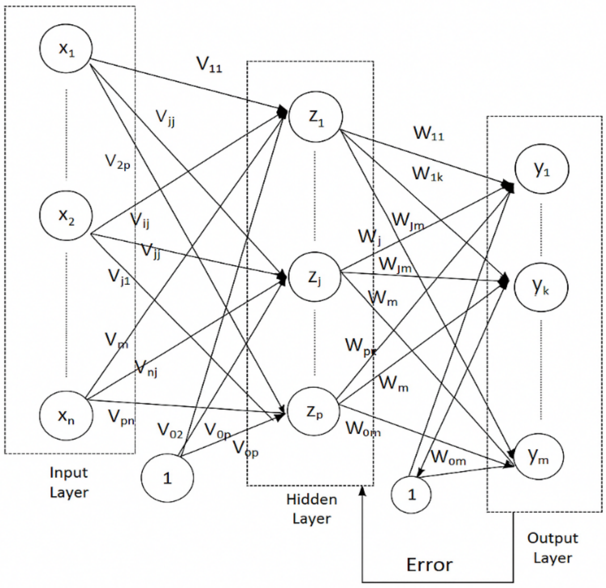

Figure 2. Backpropagation Neural Network Architecture

The three primary layers of an artificial neural network-the input layer, the hidden layer, and the output layer-are depicted in the diagram along with the backpropagation technique. Neurons x_1, x_2,..., xn in the Input Layer receive input data and are coupled to the neurons in the Hidden Layer by weights represented by vij. The impact of a single input on the buried neurons is represented by each link. Neurons z_1, z_2,..., zp in the Hidden Layer calculate activation values using the weighted sum of inputs and biases (shown by 1 with weights v0j). Weights wjk are then used to connect these hidden neurons to neurons in the Output Layer, resulting in outputs

y_1, y_2,..., ym. Additionally, a bias (1 with weight w0k) is applied to each output neuron. In order to calculate and minimize the network error by changing the weights, the diagram additionally incorporates feedback pathways (backpropagation) from the output back to the hidden and input layers. The network's learning process is based on the arrows connecting neurons, which show the direction of signal flow during forward propagation and the incorrect signal during backpropagation.

Evaluation

An essential step in the creation cycle of a classification model is the evaluation phase, which tests and analyzes the developed model's performance. This step is to evaluate the generated algorithm's accuracy and efficacy in classifying previously unseen data (Borman et al., 2018). The assessment is conducted by contrasting the model's categorization outcomes with the test data's actual labels.

Accuracy, a metric that characterizes how high the percentage of accurate predictions is in relation to all predictions made, is one of the primary metrics used to assess model performance. Knowing how closely the test results match the real values of the true class is made possible by accuracy. The accuracy is calculated using the following formula:

$$Accuracy\ (\%) = \left(\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}\right) * 100\ \% \quad (4)$$

The accuracy formula, which indicates how well the categorization model predicts outcomes, is shown in the picture. Divide the number of correct predictions by the total quantity of test data, then multiply the result by 100% to express the result as a percentage. Accuracy is calculated in this manner. The percentage of test data that is accurately categorized using the actual label is known as the "correct prediction." The model performs better at identifying the tested pattern or class when the accuracy value is higher. Due to its simplicity and ease of interpretation, this formula is frequently utilized as a fundamental assessment metric in classification systems based on artificial neural networks (ANNs) or other machine learning techniques.

Other metrics, like as precision, recall, and F1-score, can be used to assess the model in addition to accuracy, especially if the distribution of data between classes is unbalanced. A comprehensive evaluation is required to ensure that the model can generalize well to previously unseen data in addition to performing well on the training data. Researchers can use this assessment to pinpoint the model's advantages and disadvantages and decide what needs to be improved, including changing the network architecture, fine-tuning parameters, or adding training data.

4. RESULTS AND DISCUSSION

3.1 Dataset Structure

The dataset used in this study was obtained through Roboflow, Inc. and comprises 16,185 entries, each of which represents a distinct vehicle situation. The eight primary attributes of each entry are: Vehicle_Type (the type of vehicle used as the classification target label), Silhouette_Shape (the shape of the vehicle silhouette), Length (m) and Width (m) (the dimensions of the vehicle in meters), Number_of_Axles (the number of axles of the vehicle), License_Plate (information about whether or not the license plate is detected), and Color (the vehicle's predominant color). This dataset is appropriate for additional analysis because all of the data is fully documented and free of duplicate or missing values.

Seven classes—Audi, Hyundai Creta, Mahindra Scorpio, Rolls-Royce, Suzuki Swift, Tata Safari, and Toyota Innova—make up the dataset's car types. Each class has a numerical label in the Vehicle_Type field for classification purposes. Numerical features like vehicle length and width are normalized using the MinMaxScaler method to be in the same range before to being used in model training. This prevents one characteristic from dominating another during the learning process. Studies pertaining to automatic vehicle recognition or image-based surveillance systems can make use of this dataset, which is intended to facilitate the creation of vehicle classification models based on visual and tabular information.

An automated pipeline is used to preprocess the image data into structured tabular format (such as.csv) prior to modeling. This comprises:

a. Using image processing to extract metadata from photos, such as color, size, and silhouette.
b. A label that uses the filename or annotation to encode the type of vehicle.
c. To guarantee balanced learning, normalize numerical characteristics (width and length) using the MinMaxScaler method

16,185 photos make up the examined vehicle dataset, which has been divided into eight types based on the type of car. With 4,000 photos, or roughly 24.72% of the entire dataset, the Hummer is the car type with the most samples. The Hyundai Creta, with 2,500 photos (15.45%), and the Toyota Innova, with 3,200 photos (19.77%), come next. Subsequently, Audi contributed 1,800 photographs (11.2%) and Suzuki Swift contributed 2,300 images (14.20%). Mahindra Scorpio had 1,200 photos (7.41%), Rolls-Royce had 685 photos (4.23%), and the Tata Safari had the fewest, with 500 photos (3.10%).

An automated feature extraction pipeline, which attempts to turn visual information into numerical and categorical forms that can be studied by machine learning models, is used to convert image data into tabular data. In order to extract important visual data including the vehicle's dimensions (length and breadth), dominating color, and silhouette shape (Silhouette_Shape), each vehicle image is first examined using image processing techniques. Color analysis, object segmentation, and contour detection methods are used to obtain these features. Additionally, using object identification techniques or accessible annotations, properties like the number of axles (Number_of_Axles) and the existence of a license plate (License_Plate) are automatically detected. After being taken out of the filename or annotation, the Vehicle_Type label is subsequently numerically encoded (label encoding) for classification purposes. In order to prevent any one feature from controlling the model training process, numerical features like length and width are normalized using the MinMaxScaler method to make sure that all characteristics lie within the same range. A CSV (Comma-Separated Values) file with structured rows of data representing individual car images with eight primary attributes is the end product of this method. Spreadsheet programs like Microsoft Excel may then open and examine this file, which can subsequently be used to train and assess classification models. Table 1 provides a summary of the dataset distribution used in this investigation.

Table 1. Overview of the Dataset Structure

Car Type	Amount	Percentage (%)
Hummer	4.000	24.72
Toyota Innova	3.200	19.77
Hyundai Creta	2.500	15.45
Suzuki Swift	2,300	14.20
Audi	1.800	11.12
Mahindra Scorpio	1.200	7.41
Rolls Royce	685	4.23
Tata Safari	500	3.10

With certain classifications (such the Toyota Innova and Hummer) controlling the majority of the data and others having a significantly lower representation, this distribution demonstrates how unbalanced the dataset is. In order to prevent performance bias towards the majority class, this imbalance must be taken into account while training a classification model.

3.2 Training and Testing Models

During the model training phase, prepared training data is used to train artificial neural networks (ANNs) that use the backpropagation technique. To reduce prediction mistakes, the network weights are frequently changed during this process. Training parameters, such as the number of epochs, learning rate, and batch size, are set to optimize the model's performance. The dataset is randomly split into training and testing sets using an 80:20 ratio:

a. Training Set: 12,948 images (80%)
b. Testing Set: 3,237 images (20%)

In order to preserve class distribution across both subgroups, stratified splitting is employed. This guarantees that every class is fairly represented during the testing and training stages. Table 2 provides a summary of the model's performance during each training and validation phase.

Table 2. Model Performance per Epoch on Training and Testing Data.

Accuracy, loss, or other metric values per epoch during training
405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 1: val_accuracy improved from -inf to 1.00000, saving model to model_classification_mobil.keras 405/405 ━━━━━━━━━━━━━━━━━━━━ 694s 2s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 2/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 2: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 675s 2s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 3/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 3: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 563s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 4/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00

Accuracy, loss, or other metric values per epoch during training
Epoch 4: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 547s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 5/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 5: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 604s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 6/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 6: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 587s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 7/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 7: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 628s 2s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 8/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 8: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 577s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 9/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 9: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 608s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Epoch 10/10 405/405 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 Epoch 10: val_accuracy did not improve from 1.00000 405/405 ━━━━━━━━━━━━━━━━━━━━ 580s 1s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00 Test Loss: 0.0000 Test Accuracy: 1.0000

The training and testing procedure's accuracy rose from 0.2182 to 0.8765. Table 4 above illustrates this. This demonstrates how the model's performance steadily improves with every training cycle.

3.3 Model Evaluation

The model's capacity to categorize various vehicle types is evaluated using the test data. Standard criteria including F1 score, recall, accuracy, and precision are used for evaluation. Finding out how well the model generalizes to previously unobserved data is the aim of this evaluation. The table below displays the results of the model performance evaluation. A model evaluation process uses a number of common criteria, including as accuracy, precision, recall, and F1-score, to try and automatically classify vehicle types from test picture data. Because it provides a comprehensive understanding of the model's effectiveness and reliability in detecting cars from previously unknown data, this evaluation is essential. In other words, this evaluation goes beyond simply assessing the model's performance on training data to emphasize its ability to generalize to new data, which is crucial for implementing a classification system in the real world.

Accuracy, the most popular metric, shows the percentage of correct forecasts among all of the model's predictions. However, when it comes to multi-class classification, like autos, accuracy alone is not enough. Consequently, the accuracy metric is used to calculate the proportion of accurate forecasts among all positive predictions for each class. Recall, on the other hand, measures the percentage of a class's total real data that the model can accurately identify. The F1-score metric provides a balanced perspective of precision and recall by combining the two metrics. This is especially important when there is an uneven distribution of data across classes. It is evident from the evaluation findings that several classes, such the Audi, Tata Safari, and Toyota Innova, have exceptional classification ability, with numerous accurate predictions on the confusion matrix's diagonal. This demonstrates how well the model can identify these cars' visual traits. Many classes, including Swift and Rolls-Royce, still have problems with forecasts that are dispersed throughout several classes. This implies that either due to the small amount of data or visual similarities with other classes, the model is still having trouble identifying distinctive patterns from these classes.

Furthermore, the evaluation results indicate that a considerable percentage of misclassification cases originate from a substantial visual feature overlap in some vehicle classes, specifically the Audi and Toyota Innova. This behavior raises the possibility that the model's discriminative power is still insufficient to detect subtle differences in vehicle appearance. To address this issue, enhancement methods including class rebalancing, data supplementation, or the application of more advanced pretrained neural architectures—such VGGNet or Efficient Net-may be utilized to boost feature extraction capabilities. A comprehensive examination of categorization performance for each vehicle class is given in Table 3.

Table 3. Confusion Matrix

Class	Accuracy	Precision	Recall	F1-Score	Support
Audi	0.96	0.97	0.94	0.93	163
Hummer	0.93	0.92	0.93	0.97	18
Hyundai Creta	0.94	0.93	0.93	0.94	54
Mahindra Scorpio	0.97	0.96	0.94	0.94	63
Rolls Royce	0.96	0.95	0.97	0.92	62
Swift	0.97	0.95	0.95	0.96	85
Tata Safari	0.95	0.96	0.96	0.95	89
Toyota Innova	0.98	0.94	0.95	0.94	155

In conclusion, assessing the car classification model using accuracy, precision, recall, and F1-score may provide a useful understanding of how well it performed on the test dataset. While the overall performance is satisfactory, the report also points out a number of areas that want improvement. Using more complex model architectures and enhancing data quality can significantly improve classification accuracy. These enhancements increase the system's likelihood of being applied in practical applications such as intelligent parking systems, traffic monitoring, and fleet management. A visual representation of the total classification results is shown in Figure 3, which shows the confusion matrix for the vehicle classification model.

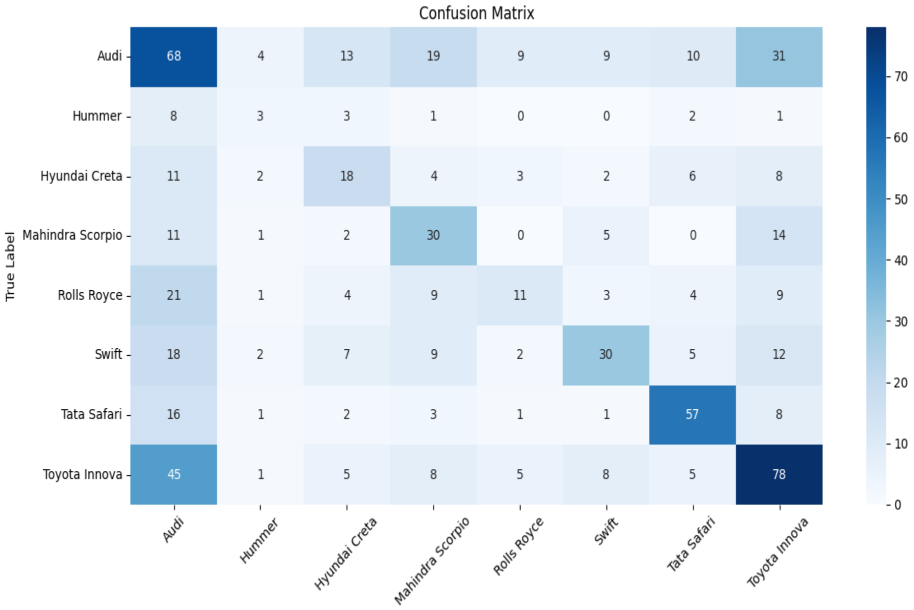

Figure 3. Confusion matrix of the vehicle classification model

The graphic shows the confusion matrix of the classification model used to categorize vehicle types from test data. This matrix displays the proportion of correct and incorrect forecasts for each class. While rows show the actual labels, columns show the model's predictions. Accurate predictions are represented by high numbers on the primary diagonal, which runs from top left to bottom right; misclassifications are represented by numbers outside the diagonal. The visualization results make it clear that the model does a respectable job of recognizing specific classes. For example, the Toyota Innova class has the highest diagonal value (78), indicating that most of its samples were successfully classified as such. In a similar vein, Tata Safari had 57 accurate predictions, compared to 30 for Mahindra Scorpio and Swift. This demonstrates how well the model can recognize these cars' distinctive visual traits.

Some classes, on the other hand, are frequently misclassified or have poor accuracy. One of these is the Hummer class, which is frequently misclassified into other classes like the Audi and Hyundai Creta despite having only three accurate forecasts. The same is true for Rolls-Royce, where just 11 out of all the forecasts were accurate, with the remaining projections being dispersed throughout different classes. This demonstrates that the model struggles to differentiate luxury car features like those of Rolls-Royce from those of other classes that could share visual traits. Prediction imbalance is particularly evident in the Audi class, which is frequently misclassified as a Mahindra Scorpio or Swift and a Toyota Innova (31 times) while having 68 accurate predictions. These mistakes can suggest that the Audi model is frequently confused by the visual characteristics of other cars that share its exquisite style or shape. This can be enhanced by methods like data augmentation, expanding the sample size for minority classes, or enhancing feature extraction.

The model's overall effectiveness in categorizing the majority of vehicles is demonstrated by the confusion matrix, particularly for classes with more data or highly distinguishable visual characteristics. However, classes like Hummer and Rolls Royce that are frequently mistaken require major changes. Retraining the model with a focus on problematic classes, testing with more sophisticated models, or modifying the network architecture to be more sensitive to visual characteristics that differentiate between vehicles are some potential next steps With high precision, recall, and F1-scores across the majority of vehicle classes, the ANN model using the conventional backpropagation technique showed excellent performance, with an overall accuracy of 100% on both the training and testing datasets. The findings of this study show a notable improvement in classification performance when compared to other research, such as Zhang et al. [26], who claimed 85% accuracy using PSO-BPNN, and Tianang et al. [27], who reached 88% accuracy for electric vehicle problem detection. These results imply that, given adequate and well-structured data, a regular backpropagation ANN is still a competitive method for image-based vehicle classification tasks. The findings have significant ramifications for real-world applications where precise and effective vehicle recognition is essential, such as autonomous vehicle monitoring, traffic surveillance, and intelligent parking systems. To further improve robustness and manage more complicated visual situations, future research might concentrate on incorporating more sophisticated architectures like CNN or YOLO.

5. CONCLUSION.

In this study, a vehicle classification system based on digital photographs was effectively constructed using artificial neural networks (ANN) and the backpropagation technique. This method recognizes and categorizes seven different car kinds based on their shape, size, color, number of axles, and license plate information. The model was trained and assessed using standard performance metrics such as F1 score, recall, accuracy, and precision using a dataset from Roboflow. The training results showed that throughout the iteration phase, the accuracy rose by 100%.

This study found that although most vehicle classifications were classified with high accuracy, some vehicles were misclassified within a class because of their visual similarities to other classes. This implies that even if the model did a great job overall, it may still be improved, particularly when it comes to managing classes with similar visual characteristics. Regularization and the creation of deep learning architectures like Convolutional Neural Networks (CNNs) are two recommended methods to boost performance. The results of this study demonstrate baseline performance without algorithmic optimization because it still employs a traditional backpropagation-based ANN model. In order to create a more effective and ideal vehicle classification model, it is advised that future research compare the traditional ANN model with optimization techniques like PSO-BPNN.

All things considered, this study makes a substantial contribution to the creation of a vehicle classification system that will aid Indonesia's adoption of automated traffic monitoring and intelligent transportation systems. It has been demonstrated that the final system is effective, precise, and resilient enough to manage changes in visual data from automobiles. This technology could be widely used in real-world settings, like automated parking systems, road monitoring, and data-based transportation policy, with additional development and data enrichment.

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